Denoising Techniques for EEG Signals: A Review

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Abstract - *An EEG signal is a brief recording of the brain's spontaneous electrical activity. EEG measures and evaluates signals generated by the bombardment of neurons within the brain. EEG signals possess small amplitude of the order of micro volts that are contaminated by a variety of noises known as artifacts. These artifacts include ocular artifacts, power-line interference, breathing, and muscle activities. These signals are employed to diagnose various types of brain disorders such as epilepsy, stroke, tumors, sleep apnea, and parasomnia; therefore, these signals must be free from artifacts for proper analysis and detection of these diseases. To eliminate these artifacts from the recorded EEG signals, numerous EEG denoising methods such as regression, blind source separation (BSS), wavelet transform (WT), empirical mode decomposition (EMD) have been presented by the researchers in the literature. In this paper, detailed reviews of these techniques have been presented.*

Key Words: Artifacts, Blind source separation, Brain disorder, Electroencephalogram, EMD.

1.INTRODUCTION

Electroencephalography (EEG) signal is the term for the measurement of spontaneous brain impulses in the human brain [1], [2]. The nervous system communicates in an electric language. The nerve cells inside the human brain perform tasks by adapting the transmission of electrical currents across the membranes. These electrical currents generate electric and magnetic fields can be captured from the scalp's surface using electrodes [3]. The Electroencephalogram (EEG), which is a recording of the electrical activity of the brain, is made by amplifying the potential differences between several electrodes. In EEG, electrodes are often positioned on a person's scalp in order to record the electrical activity of the cerebral cortex's nerve cells. EEG often identifies the signals produced when billions of neurons are active at once rather than recording the activity of a single neuron. It primarily captures the signal coming from the tiny portion of the brain that surrounds each electrode. Neurotransmitters binding to receptors on the postsynaptic membrane cause changes in membrane potential, which are typically measured by EEG. EEG recordings show the brain signals as waves with different amplitudes, frequencies, and shapes. It can be used to track brain activity that takes place during an event, such as finishing a task without the presence of a particular event. The EEG is employed in several clinical applications such as epileptic seizure detection, sleep disorders, tumors, stroke, and other brain dysfunction. The brain, the central part of the nervous system, controls the coordination between human muscles and nerves. EEG is a popular non-invasive tool for interpreting the complexities of the human brain due to its low cost, easy to use, and high temporal resolution. Brain death is also interpreted and detected using an EEG signal. As EEG monitors the electrical activity of the brain in large groups of neurons, it is difficult to pinpoint the activity seen using EEG to a precise location in the brain.

The analysis of long-term EEG recording is a challenging task. The EEG signal possesses a low amplitude of the order of a few micro volts to 100 micro volts and a frequency range from a few Hz to 100 Hz [4]. Depending upon amplitude level and frequency range [5], [6], the EEG signal can be categorised into five frequency bands, whose description is shown in Table 1. These brain waves represent various mental conditions of the patient. As EEG signal is having a low amplitude of the order of microvolt that can be easily contaminated by various artefacts. These artefacts can be of intrinsic types or extrinsic types.

Table 1: Five frequency rhythms of EEG signal

Frequency band	Frequency (Hz)	Amplitude (μV)	Brain Activity
Delta	0.5-4	20- 200	Deep Sleeping
Theta	4-7	Less than 20	Dreaming: Meditation
Alpha	8-13	30-50	Relaxed, Eye closed
Beta	13-30	5-30	thinking, cognition, high alert
Gamma	Greater than 30	Greater than 50	Consciousness

Various artefacts have been eliminated by maintaining an appropriate recording environment and conducting experiments under the supervision of clinical experts [7]. A variety of approaches can be employed to eliminate artefacts from the recorded EEG signals and enhance the signal-to-noise (SNR) ratio of the input signal. One of the most fundamental approaches is simple signal averaging. The underlying assumption of signal averaging is that while the signal of interest is provided and steady, the artefacts contained in the recorded signal are random [8]. The drawback of signal averaging is that it cannot be applicable to non-stationary signals like EEG signals, which are of interest. Another option is to simply discard contaminated EEG epochs. However, in this method, the recorded data is manually reviewed, analysed and interpreted the contaminated segments, and then finally rejected those segments from the recorded EEG signals [9], [10]. When there is a high level of contamination, this process is time-consuming and results in the loss of significant information hidden in the original signal. The primary goal of any denoising approach is to eliminate the level of artefacts while preserving the original information of the recorded signal.

2. TECHNIQUES FOR DENOISING EEG SIGNALS

2.1 Regression Method

It is one of the commonly used approaches for eliminating ocular artefacts for instance eye blinks and movements. Both the time domain and the frequency domain are used with this technique [11], [12]. The performance of this method depends on simultaneous monitoring of EEG and EOG recordings to determine those parameters that characterize the existence of EOG artefacts in the EEG recordings. This can be achieved using a regression parameter, β which computes an estimation of the proportion of artefacts in the specific EEG channel. The correct procedure must involve subtraction of the estimated value of EOG artefacts from the recorded EEG signals [13], [14].

$$s(t) = x(t) - \sum_{a=0}^{T} \beta_a \; y(t-a)$$

Where $x(t)$ represents the recorded EEG signal at time t, and $y(t-a)$ denotes EOG information at $(t-a)$ time. β denotes the regression coefficients and $s(t)$ represents the uncorrupted EEG data at time t. The major drawback of this technique is that it can eliminate ocular artifacts effectively but fails to remove other artefacts such as EMG artefacts, power-line interference, and baseline wander noise. This method does not possess any reference channels.

2.2 Blind Source Separation (BSS)

BSS refers to a group of algorithms that have recently gained prominence in the elimination of artefacts from recorded EEG signals. This method involves recovering source data from a linear mixture of recording channels with no prior knowledge of the source signal. The ability to identify source signal either as true EEG signal or any corrupted signal allows for the removal of artefacts without losing any significant information from the recorded EEG signals [15]. The BSS algorithm consists of three main steps: separating the source signal from a linear mixture, recognising of artefactual signal, and finally eliminating the artefacts from the original signals by preserving the relevant information. A number of BSS algorithms have been distinct on the basis of degree of signal separation. Although numerous algorithms have been discussed in the literature to perform BSS, out of these, principal component analysis and independent component analysis are commonly used techniques for the separation of source signals. The algorithm is selected based on the three parameters: artefact type, taint level, and target signal [16]. Two commonly used BSS techniques in signal processing are:

2.2.1 Principal Component Analysis (PCA): One of the most efficient techniques for the separation of correlated mixtures is PCA if the sources are statistically uncorrelated [17]. PCA retrieves the uncorrelated signal from a linear mixture using second-order statistics. This method employs Singular Value Decomposition (SVD) to find the first principal components P_1, P_2, ……., P_K that reveal a greater amount of variance possessed by K number of linearly transformed components. The direction in which the input variables have maximum variance is selected as the first principal component. The second principal components are orthogonal to the first component. PCA is a dimensional reduction technique that retained the main information of the original signals [18]. PCA is employed to create spatial filters for the removal of artifacts from the recorded EEG signals [19]. PCA-based filters show better performance in comparison to the regression method while removing artifacts from original EEG signals, but this technique fails to distinct the ocular artifacts from the EEG signals if both have same amplitudes.

2.2.2 Independent Component Analysis (ICA): In 1986, Harault and Jutten introduced a new technique known as ICA, an advanced version of PCA, which uncorrelated the source signals using higher order statistics. It transforms a set of vectors into maximally independent components. ICA, based on two assumptions namely, independent components are non-Gaussian and minimization of mutual information [20], is employed to recover the original information that is statistically independent. Numerous algorithms based on ICA have been discussed in the literature, out of which only a few ICA models are employed for processing non-stationary signals such as EEG, and ECG signals [21], [22]. The disadvantage of this method is that it needs a manual selection of artefactual components from estimated variables for corrective measures.

2.3 WAVELET ANALYSIS

A wavelet is a basic function that acts as a window function. The wavelet transform utilizes a set of functions, known as decomposition of a wavelet function, to express a signal. The signal decomposition is carried out using a set of coefficients known as wavelet coefficients. The coefficients are called detailed and approximate coefficients. A wavelet transform (WT) is a time-frequency approach in which the signal is analyzed into different frequencies at different resolutions, which is known as multiresolution analysis [23]. For high frequency components, the WT provides strong time resolution but weak frequency resolution. For low-frequency components, it provides descent frequency resolution but subpar poor time resolution.

$$F(\tau,s) = \frac{1}{\sqrt{|s|}} \int_{-\propto}^{\propto} f(t)\, \psi^{*} \frac{(t-\tau)}{s} dt$$

In the above equation, the symbol, τ, represents the shifting parameter in the time domain while the symbol, s, represents the scaling in the frequency domain. The WT provides better time-frequency localization features in comparison to the short-time Fourier transform (STFT) that are more suitable for transient analysis as well as time-varying behavior of non-stationary signals such as ECG, and EEG signals [24].

In general, a wavelet-based approach involves the following steps for denoising or analyzing a non-stationary signal:

i) Signal decomposition using a suitable mother wavelet and decomposition level.
ii) Selecting threshold value for wavelet coefficients
iii) Take inverse wavelet transform to reconstruct the original signal.

A discrete wavelet transform during denoising of EEG signals utilizes two parameters namely scaling, a and translation, b of the mother wavelet, ψ(t).

$$\psi(a,b)(t) = 2^{\frac{a}{2}}\, \psi(2^{a}t - b)$$

The main limitation of WT is that it is difficult to select the type of mother wavelet, thresholding value, and number of decomposition levels.

2.3 EMPIRICAL MODE DECOMPOSITION (EMD)

EMD is an adaptive signal decomposition method employed for the analysis of non-stationary signals such as EEG signals. In 1998, N. E. Huang introduced this method which employs the concept of instantaneous frequency explained by the Hilbert Huang Transform (HHT) [25]. HHT is composed of two sections: empirical mode decomposition followed by Hilbert transform. The EMD technique decomposed the non-stationary EEG signals into a set of narrow-band components which as commonly known as intrinsic band functions (IMFs). This technique employs a sifting process to extract the IMFs from the EEG signal. Each IMF has to satisfy the following two criteria:

i) For the entire data set, the difference between a number of extrema and number of zero crossings should be either equal to zero or they should differ at the most by 1.
ii) At any instant of time, the average value of the upper and lower envelope defined by local maxima and minima should be zero.

Using Hilbert transform, each IMF provides instantaneous frequency as a function of time that represents acute recognition of embedded structures. It has been noticed in the literature that those noise components normally found in the first few IMFs when a signal is analyzed using the EMD technique [26]. Although EMD is an efficient and adaptive method for signal decomposition, it suffers from many limitations that include mode mixing, end effect artifacts, scale alignment problems, and non-orthogonality while extracting IMFs from the non-stationary signals. The orthogonality problem has been solved using an orthogonal and energy-preserving EMD algorithm [27]. Scale alignment issue is resolved using the Multivariate EMD approach [28] still this method possesses a lack of mathematical completeness and is completely based on the expedient procedure.

3. DISCUSSION

The analysis of the human brain has been greatly impacted by the use of EEG in the realm of clinical research. The EEG signal is tainted with a variety of artifacts, as was already mentioned. EEG signal denoising techniques come in a variety with various benefits and drawbacks. These techniques work well in a certain domain and with specific artifacts. For example, the ocular-related artifacts can be eliminated effectively using the regression method. If the EEG signal is contaminated with other types of artifacts, this method fails to eliminate these artifacts. Besides this, this method utilizes one or more EOG channels. As a consequence of this, this method also cancels out the neural potential available in the EOG channel while eliminating ocular-based artifacts. The problems encountered in the regression method are eliminated using the principal component analysis approach (PCA). The limitation of this method is that if the artifacts present in EEG signals possess approximate amplitudes, it fails to eliminate the artifacts. To recover uncorrelated signals, PCA uses second order statistics; higher order statistics are ineffective.

This can be avoided by using the independent component analysis (ICA) approach, which is based on blind source separation. The idea of distinguishing distinct components underlies the ICA approach. This technique can be used to isolate and get rid of many different forms of EEG artifacts. The modified extension of PCA is known as ICA. The ICA approach can be used to remove EEG artifacts in a variety of situations. It is one of the most used techniques. Complicated computations and manual selection of unrelated independent components are two of this method's drawbacks. In addition, while EEG artifacts vary in the frequency domain, ICA operates in the time domain. After this, Wavelet transform came into existence that can represent a signal in time as well as frequency domain. This method possesses better time-frequency localization as compared to the short-time Fourier transform method. This method decomposes the EEG signal into low and high-frequency components. Low-frequency components are called approximate wavelet coefficients and high-frequency components are referred to as detailed coefficients. By applying thresholding, various artifacts can be eliminated from the recorded signals and the filtered signal is reconstructed. The selection of proper mother wavelet and level of decomposition levels is still difficult to apply, which is the prime limitation of the wavelet method. In literature, many authors employed a combination of two methods to effectively eliminate the artifacts. In 2005, Berg et al. [29] employed a wavelet-ICA based approach for filtering the noise from the recorded signal. In 2007, Inuso et al. [30] proposed the same technique for the filtering of electromyogram (EMG) signals.
The empirical mode decomposition method, an efficient method for analysis of non-stationary EEG signal, is employed to recover the original signal from the recorded signal intermingled with noise and artifacts. The artifacts are eliminated from the recorded signal using the EMD method while preserving the original contents hidden in the signal.

4. CONCLUSION

In this study, various techniques for eliminating artifacts from EEG signals are described.

These come with benefits and drawbacks. Combining the algorithms of two or more current approaches helps address these constraints. These algorithms can get over each other's limitations and provide more superior and useful outcomes than they would as standalone algorithms. This is because EEG artifacts vary in the frequency domain whereas ICA operates in the time domain.

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